Ischemia Detection using Supervised Learning for Hierarchical Neural Networks based on Kohonen-maps

L. Vladutu, S. Papadimitriou, S. Mavroudi and A. Bezerianos
Medical Physics Department, Medical School, University of Patras, Greece

Abstract— **The detection of ischemic episodes is a difficult pattern classification problem. The motivation for developing the Supervising Network - Self Organizing Map (sNet-SOM) model is to design computationally effective solutions for the particular problem of ischemia detection and other similar applications. The sNet-SOM uses unsupervised learning for the regions where the classification is not ambiguous and supervised for the "difficult" ones- in a two-stage learning process. The unsupervised learning approach extends and adapts the Self-Organizing Map (SOM) algorithm of Kohonen. The basic SOM is modified with a dynamic expansion process controlled with an entropy based criterion that allows the adaptive formation of the proper SOM structure. This extension proceeds until the total number of training patterns that are mapped to neurons with high entropy (therefore with ambiguous classification) reduces to a size manageable numerically with a proper supervised model. The second learning phase (supervised training) has the objective of constructing better decision boundaries of the ambiguous regions. In this phase, a special supervised network is trained for the task of reduced computationally complexity- to perform the classification only of the ambiguous regions. After we tried with different classes of supervised networks , we obtained the best results with the Support Vector Machines (SVM) as local experts.**

Keywords— **Self-Organizing Maps, Ischemia, Entropy, Principal Component Analysis, Divide and Conquer algorithms, Radial Basis Functions, Vapnik-Chervonenkis Dimension, Support Vector Machines, Computational Complexity**

I. INTRODUCTION

MYOCARDIAL ischemia (MI) is caused when the contractile cells of myocardium are not provided with the sufficient amount of oxygen and nutrients. Frequently, when is not detected in an incipient phase, MI can develop myocardial infarction with its severe consequence of heart failure and arrhythmia that may even lead to patient death. The capability of accurate and early detection of an acute ischemic event is critical for the assessment of a proper treatment. The Electrocardiogram (ECG) represents a recording of the changes occurring in the electrical potentials between different sites on the skin, where the electrodes are placed, as a result of the cardiac activity. Since the ECG is recorded easily and noninvasively, it becomes important for us to use ECG analysis to provide means for reliable ischemia detection. We tried in the research work whose results are presented, to avoid the utilization of local, isolated features of the ST-T Complex, often influenced by noise, by relying on the Principal Component Analysis (PCA) technique [1] for extracting PCA coefficients (features) that describe the global content of the ST-T Complex. The PCA coefficients are used to train the Supervising Network Self-Organizing Map (sNet-SOM). The sNet-SOM uses a SOM based unsupervised algorithm [2], [3] in order to "learn" the structure of the state space corresponding to the problem under analysis.

The neural network model of sNet-SOM is an extension of the Self-Organizing Map of Kohonen [2], [4] and is our proposal for solving difficult classification problems especially those where there is no a priori information available (for 'ad initio' state space partitioning). The sNet-SOM utilizes a SOM unsupervised algorithm [2], [3] in order to learn the structure of the problem state space. In the state space regions where classes can be well separated (unambiguous or "simple" regions), the unsupervised learning phase creates neurons that represent unambiguously their class and therefore it can be used to perform the classification task directly. In contrast, in regions where different classes overlap, or patterns of different classes lie very close and cannot be separated by linear hyperplanes (i.e. ambiguous or "difficult" regions), a supervised learning scheme is used to enforce complex decision boundaries.

The specialized SOM that forms the "kernel" of the sNet-SOM is referred by us as Classification Partition SOM (CP-SOM). The CP-SOM modifies the original SOM algorithm with a dynamic expansion process controlled by an entropy based criterion. This extension continues until the total number of training patterns that are mapped to neurons with high entropy (and therefore to ambiguous classification) reduces to a size that can be managed to a proper supervised model effectively (this determines the upper bound) and is sufficient for valid generalization (this determines the lower bound). We used for our evaluation data from "The European ST-T Database", [5], [6], which includes two channels from Holter recordings corresponding to 79 patients with ischemic episodes of all types. Cardiology specialists have annotated the ischemic episodes in the original database.

The paper proceeds as follows: Section II describes methodology, i.e. the stages of preprocessing applied to the ECG signals of the European ST-T database recordings. The purpose of these steps is to create an effective

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description of the ST-T Complex to form the input to the neural classification devices.

Section III initially outlines the results and the architecture of sNet-SOM. Subsequently, it also describes the extensions to the SOM that lead to the Classification Partition Self-Organizing Map (CP-SOM). Further on, section III deals with the design of the supervised part of the sNet-SOM and proposes the combination of CP-SOM with Support Vector Machines (SVMs)-used as local experts, as the most effective model from those that we used.

Section IV discusses the results of the classification effectiveness of the plain SOM and compares them with the obtained performance after the utilization of the additional supervised stage.

Finally, Section V presents the conclusions along with some directions onto which further research can proceed for improvements.

II. METHODOLOGY

Extraction of ST-T Complexes

The aim of the ECG signal preprocessing is to prepare a compact description of the ST-T complex, which is composed from the ST segment and the T-wave, for the input of the sNet-SOM, with minimum loss of information. The ECG signals from the European ST-T Database are a set of long-term Holder recordings provided by eight countries [5], [6]. The training set is extracted from 110 fifteen minutes ECG records, consisting of representative normal and abnormal ST-T waveforms. After R-peak detection (inside the QRS complex) using the amplitude and the first derivative of the signal, [9] and baseline wander rejection (based on cubic splines) we could precisely extract the ST-T patterns for PCA feature extraction [7], [8].

Principal Component Analysis

We selected the Principal Component Analysis (PCA) transformation as the tool for reducing the dimensionality of the extracted ST-T samples, because it permits an optimal reconstruction of the original data in the mean-square error sense (subject to the dimensionality constraint). In the time series representation of the PC's (the principal components) the ischemic episodes appear as peaks, as we represented in the Figure 2.

In order to reject the influence of artefacted beats, we used two simple, yet effective ways: first- to feed the inputs of sNet-SOM in an original way: instead of giving the 5 PC's from a single beat, we've chosen the solution to input the 35 PC's resulted from PCA coming from a burst of 5 successive beats (it resulted 35, because the PC's of the central one are taken 3 times). In this way, of course, the PC's from the central beat had the highest weights. Following the extraction of principal components a noise reduction approach is used to improve the classification performance of these coefficients. The selected noise reduction approach relies on the possibility that we have to modify the properties of the PCA coefficients signal by processing its Wavelet Transform (WT) modulus maxima and to reconstruct the corresponding function [13], [14], [15], [16]. As a result of the utilization of Wavelet based denoising in the domain of Principal Component coefficients we obtained a slight improvement of the classification performance. The denoised PCA projection coefficients are then fed to the sNet-SOM nonlinear device in order to perform the complex (and highly nonlinear) classification decision about the category pertaining to each analysis case (i.e. normal, abnormal).

TABLE I

The average ischemia episode detection performance evaluated with the corresponding networks (i.e. SOM, sNet-SOM with RBF as supervised expert and sNet-SOM with SVM as supervised expert

Network Type	Ischemia Episode Sensitivity	Ischemia Episode Predictivity
SOM	74.9%	73.7%
sNetSOM RBF	79.5%	77.6%
sNetSOM SVM	82.8%	82.4%

III. RESULTS

The training set consists of 9,000 ST-T Complexes extracted from about 32,000 beats. This set is constructed by using samples taken from 8 records (different from those that we used for the testing sets). The two classes (i.e. normal and ischemic) are represented by an approximately equal number of samples in the training set, in order to avoid the "biasing" of the classification device toward a specific class. For each record, a number of ST-T Complexes from its start (e.g. the first 80) is used to compute the average level of the PCA series. We select for the training set only records with stable baseline levels. However, in the test sets the average level that is computed from the initial beats is subsequently updated on every point with a moving average algorithm. This operation is stopped in the presence of either an ST-T episode or an artefact. In this case a new average PCA level is estimated.

The trained networks decide on windows consisting of 5 beats, for whether or not the beat at the center of the window (i.e. the 3rd) is ischemic. As already presented, the central beat, b_n, is repeated three times at the input in order to increase its significance and thus the input considers the Principal Components for 7 beats. Thus, by feeding three times the central beat, the input becomes of the form:

$$\left(b_{n-2} \quad b_{n-1} \quad b_n \quad b_n \quad b_n \quad b_{n+1} \quad b_{n+2} \right)$$

The classification operation is repeated by shifting the 5 beat window over the whole testing set in order to classify every beat.

ST-T episodes should consist of a minimum number of consecutive beats. Thus, a duration criterion is also introduced, and very short ST-T episodes are rejected (as "false ischemic episodes"). Since physicians take care only of the ST-T episodes lasting at least 15 seconds, the duration threshold was set to 15 seconds. Additionally, two adjacent ST-T episodes are considered as one if their time

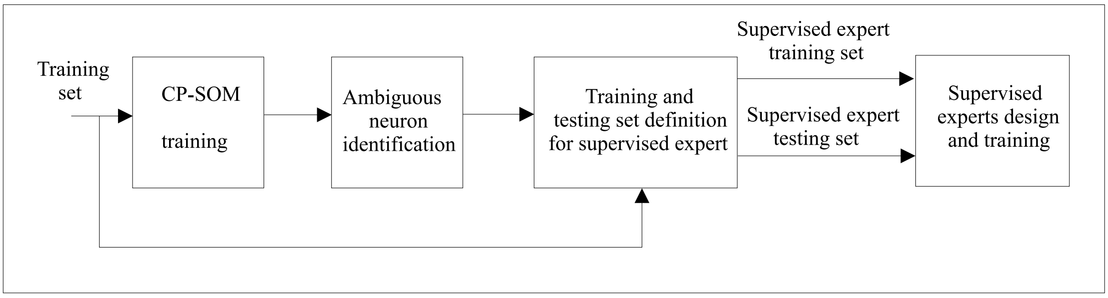

Fig. 1. Main steps for sNet-SOM training. After CP-SOM training, ambiguous neurons are identified. For each one, local training and local testing sets are created. Finally, local experts for each ambiguous neuron, are created and trained.

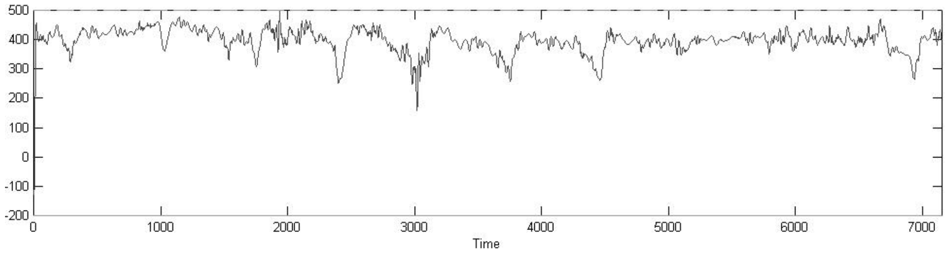

Fig. 2. Plot of denoised PC time series obtained from recording e0103 with wavelet soft-thresholding

separation is shorter than 5 seconds. A ST-T episode labeled by our classification device as positive is taken as correctly detected if it overlapped at least 50% with the annotated ST-T episode.

Otherwise, it is considered as a false positive.

The evaluation of the SOM and the sNet-SOM models has been performed on another 27 records out of the 90 records of the European ST-T database. From these records testing sets have been constructed. The whole test set contains principal component projection coefficients from approximately 250,000 ECG beats.

The classification performance ratio is a global one: it expresses the ratio of correct classifications to the total ones. For comparison we have evaluated the performances of the standard SOM algorithm on these recordings. The SOM already performs well given that it has an increased size in order to perform the classification directly. The related performances are described in the table I (Discussion section). These results have been obtained by using a SOM organized as a 10x10 lattice of neurons. The performed experiments have illustrated that this size yields the best results for direct classification. Also, we obtained better results using the Manhattan distance measure [2] in comparison to those obtained with the alternative Euclidean measure. Although the SOM is trained with the usual SOM unsupervised training algorithm [2], it has the potential to obtain a classification accuracy close to those reported in [10], [11], [12] with supervised neural models.

The results for ischemia beat classification obtained from the sNet-SOM with a Radial Basis Function network as a supervised expert are better than those obtained with a plain SOM. The training set size corresponding to the number of training set patterns mapped to ambiguous neurons was configured to 2000 and the number of centers is 500. Also, the regularization parameter- see also [1], [17]- λ, was chosen as 0.1. The CP-SOM has grown to a two-dimensional lattice of neurons of size 4x4. The average beat classification accuracy of the RBF network as a supervised expert is 76.51%.

The table I displays the corresponding results with a Support Vector Machine (SVM) as a supervised expert. The training set for the SVM case is the same as for the RBF. The inner-product kernel of the SVM is based on a polynomial kernel of degree $d = 3$, and a regularization parameter of $C = 10$. The CP-SOM is of the same size (i.e. 4X4 lattice). The average beat classification performance has been improved to 80.4%.

We defined the ischemic episodes in terms of ischemic beats according to the same set of criteria as those used in [10]. Correctly detected episodes are termed True Positive (TP) episodes. Missed episodes are termed False Negatives (FN). Also, when a nonischemic episode is detected as ischemic, a False Positive (FP) situation has occurred. The *ST-T Episode Sensitivity* is defined as the ratio of the number of detected episodes matching the database annotations to the number of annotated episodes. In terms of the above definitions:

$$\text{Sensitivity} = (TP)/(TP + FN)$$

Another important index is the *ST-T Episode Predictivity* which is defined as the number of correctly detected episodes to the total number of episodes detected, i.e.

$$\text{Predictivity} = (TP)/(TP + FP)$$

Table I displays the results of the average ischemia episode detection performance evaluated with the three network types. The second column displays the sensitivity

while the third one the predictivity of episode detection. As it is expected from the beat classification results, the sNet-SOM with SVM as supervised expert yields a better average episode detection performance. Generally, the results we have obtained are close to the results reported by other authors [10], [11], [12]. At the SVM case we can claim that we have a small improvement of the detection ability. However, the strong point of the presented work is the framework that it provides for designing computationally efficient solutions.

IV. DISCUSSION

This work has proposed a new supervised extension to the Self-Organizing Map (SOM) model [2], [3], [4] that is called the supervised Network Self-Organizing Map (sNet-SOM). This model exploits the ordering potential of the SOM in order to split the global state space into two subspaces. The first subspace corresponds to regions over which the classification task can be performed directly with the unsupervised SOM algorithm. For the second subspace though, complex decision boundaries should be enforced and the generalization performance should be explicitly designed. The SOM algorithm is not appropriate for this task and therefore supervised training networks capable of achieving good generalization performance (i.e. Radial Basis Functions and the Support Vector Machines) are used. We have developed the sNet-SOM with Radial Basis Function networks [1], [17], and Support Vector Machines as supervised experts [1], [19]. All these designs construct approximations that involve local fitting to the dynamics of the target function. The locality of these networks fits well with the locality of the subspaces that constitute the ambiguous region. The RBF networks address the issue of regularization in a disciplined mathematical way through the Tikhonov regularization theory [17], [20]. The Support Vector Machines have obtained the best discrimination capability for the ambiguous regions (Table I).

V. CONCLUSION

The main objective of using sNet-SOM for difficult pattern classification tasks is to obtain significant computational benefits in large scale problems. The sNet-SOM utilizes the computationally effective SOM algorithm for resolving most of the regions of the state space while it uses advanced supervised learning algorithms to confront with the difficulties of enforcing complex decision boundaries over regions characterized by class ambiguity (quantified with the entropy criterion). Moreover, without a kind of divide and conquer approach (as the one of sNet-SOM) it is difficult to approach directly some large problems with nearly optimal models, as the Support Vector Machines, due to the computational complexity of their numerical solution.

The sNet-SOM is a modular architecture that can be improved along many directions. The utilization of different frameworks for self-organization as the Adaptive Subspace Self-Organizing Map (ASOM) [2] and information theoretic frameworks for self-organization [2], [18] can improve the phase of the state space partitioning. All these research efforts on the sNet-SOM are with the general philosophy that the best network architecture depends on the structure of the problem that is confronted. In view of that, for complex problems with irregular state spaces a device capable of integrating effectively multiple architectures as the presented sNet-SOM can perform better than individual architectures.

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